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An Intelligent System for Forest Fire Detection and Reforestation Planning

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Abstract- Forest fire incidents cause severe damage to natural ecosystems, wildlife habitats, and human life, making rapid identification a quibbling requisite for telling excuse and disaster response. Conventional fire monitoring formulation such as enchiridion surveillance, satellite observation, and sensor-based method rarely face inquiring affiliated to delayed response, high operational cost, and limited coverage. To surmount these terminal point, this line proposes an intelligent image-based system for detection of woodland fire using deep learning techniques. The system categorizes forest images into three distinct classes—Fire, Smoke, and Normal—to support early-stage fire recognition. An ensemble of advanced architectures, namely ConvNeXt-Tiny, EfficientNetV2, and Swin Transformer, is exploited to capture fine-grained visual features as well as broader contextual information. A diverse dataset of forest appearance obtained from publicly gettable sources is utilized, along with extensive preprocessing and data augmentation to enhance model strength low-level varied biological science conditions. Input images are resized and normalized before being processed by the trained models, and final predictions are determined using probability-based decision fusion. Experimental evaluation shows that the proposed approach achieves an overall accuracy of 98% on the test dataset, with consistently high precision and recall across all categories. The resolution establish that the system can reliably identify fire and smoke scenarios while reducing false detections, constituent it desirable for real-time forest monitoring and early warning applications.

Keywords: Forest Fire Detection, Deep Learning, Image Classification, ConvNeXt, EfficientNetV2, Swin.

I. INTRODUCTION

Vegetation fires symbolize one of the most annihilating biology endangerments, leading to severe damage to natural ecosystems, wildlife, and human settlements. In recent decades, the occurrence and intensity of woods fires have exaggerated substantially because of element such as climate change, extended dry seasons, rising global temperatures, and human-induced activities. These incidents result not only in the loss of forest resources but also in increased air pollution, reducing damage and supporting effective disaster response mechanisms.

Conventional forest fire monitoring techniques typically involve manual observation, watchtower surveillance, satellite-based monitoring, or sensor-driven systems. Although these methods have been widely adopted, they rarely visage objection such as delayed detection, high initiation and mending costs, limited geographical coverage, and reduced reliability under unfavorable weather conditions. Satellite-based systems, while capable of observing large forest regions, may suffer from low worldly resoluteness and obstruction origination by cloud cover. Similarly, ground-based sensors may be ineffective in remote or difficult-to-access forest areas, limiting their practical deployment.

With the rapid progress in ai, dl techniques have emerged as powerful tools for automating forest fire detection using visual information. Image-based detection systems are capable of continuously analyzing forest scenes and identifying early warning signs such as smoke formation or small fire regions before the fire spreads extensively. CNNs have proven effective in learning discriminative visual features, while Transformer-based architectures offer enhanced capability in modeling long-range and global contextual relationships within images.

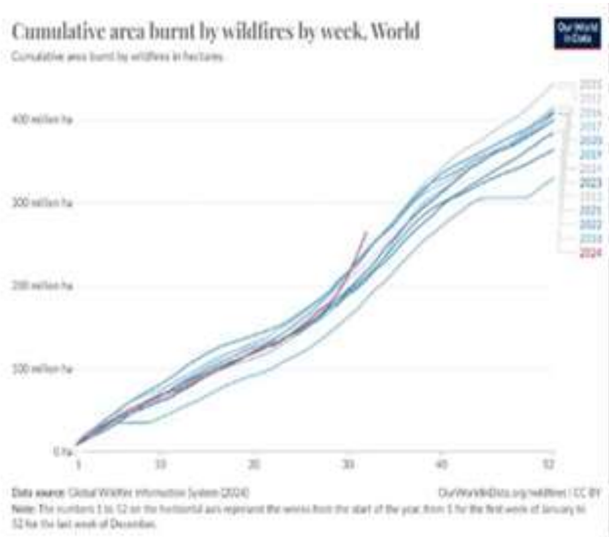

Figure 1: Trend of Forest Fire Incidents Over Recent Years

The figure illustrates the rising trend in forest fire incidents observed across the globe in recent years. This increase can largely be attributed to climate-related factors, prolonged drought conditions, higher ambient temperatures, and increased human activity. The growing frequency of such incidents emphasizes the need for intelligent and automated fire detection systems that can support early identification and prompt response.

Motivated by these observations, this research presents a deep learning–based forest fire detection framework that combines ConvNeXt-Tiny, EfficientNetV2, and Swin Transformer architectures. By integrating convolutional and transformer-based models, the proposed system captures both fine-grained local features and broader contextual information from forest images. The framework classifies images into three categories—Fire, Smoke,

and Normal—demonstrating high truth and strong induction performance. This approach offers a scalable and reliable solution for early forest fire detection, contributing to improved forest monitoring and management.

Problem Statement

The increasing frequency and severity of forest fires pose a significant threat to environmental sustainability, wildlife preservation, and human safety. Existing fire detection approaches, including manual surveillance, satellite observation, and sensor-based systems, often endure from postponed reaction times, high operational costs, and limited effectiveness in complex environmental conditions. These shortcomings reduce the ability to detect fires at an early stage, allowing them to spread rapidly and cause extensive damage.

With the growing availability of optical data prevail from surveillance cameras, drones, and monitoring systems, there is a strong need for an intelligent and automated solution capable of accurately analyzing forest images. This research focuses on addressing this challenge by developing a deep learning–based classification system that categorizes forest scenes into Fire, Smoke, and Normal classes. The proposed approach aims to provide timely alerts and support efficient fire management strategies through accurate and reliable detection

Objectives

- To design and implement an intelligent forest fire detection framework based on dl, capable of categorizing forest images into Fire, Smoke, and Normal classes with high reliability.
- To develop a robust image preprocessing workflow that improves visual clarity and provides uniform input representation for dl models across diverse environmental and lighting conditions.
- To incorporate multiple advanced dl architectures, including ConvNeXt-Tiny, EfficientNetV2, and Swin Transformer, in order to enhance feature extraction capability and overall detection performance.
- To evaluate how well the proposed approach performs using widely accepted evaluation metrics such as accuracy, precision, recall, and F1-score, ensuring dependable performance in real-world scenarios.
- To establish an early alert mechanism that supports prompt decision-making and contributes to reducing environmental damage

as well as threats to human safety caused by forest fire incidents.

II. RELATED WORK

1. Muhammad Rashid et al. (2020) proposed an image-based automated forest fire monitoring method employing cnn to recognize fire occurrences fire and smoke patterns from surveillance images. Their work focused on improving early detection accuracy by training the model on diverse forest scenes. The study demonstrated that CNN-based approaches outperform traditional color and motion- based fire detection techniques, especially under varying lighting and weather conditions, which make it suitable for real-time forest monitoring applications.

2. Yaqin Zhang et al. (2020) colleagues explored deep learning-based approaches for wildfire smoke detection using large-scale image datasets. Their approach emphasized detecting early-stage smoke rather than visible flames, which is critical for early warning systems. The results showed that CNN architectures significantly improved recall rates for smoke detection when evaluated against traditional handcrafted feature extraction techniques, highlighting the importance of automated feature learning in wildfire surveillance.
3. Harkat Gupta et al. (2021) developed a vision-based wildfire detection system by leveraging tl with pretrained CNN models. By fine-tuning models such as ResNet and VGG on forest fire datasets, the study achieved high classification accuracy. The authors emphasized that transfer learning significantly minimizes the required training duration and data requirements while maintaining strong performance, making it practical for deployment in resource-constrained environments.
4. Ahmed R. Hossain et al. (2021) and co-authors investigated smoke and fire detection in forest environments using deep learning and image segmentation techniques. Their system focused on separating fire and smoke regions from complex backgrounds. The results showed improved detection performance in cluttered forest scenes, demonstrating the advantage of combining classification and segmentation for more precise wildfire identification.
5. Xinyu Li et al. (2021) introduced a real-time wildfire detection system by using deep CNN applied to video streams. The study highlighted the significance of temporal information in fire detection. Their approach successfully reduced false alarms caused by sunlight and fog, making it suitable for continuous forest surveillance using cameras and drones.
6. R. Karthik et al. (2022) and colleagues presented a deep learning–based fire detection system using EfficientNet architectures. Their work demonstrated that EfficientNet models that deliver broad spotting demonstration while safekeeping computational costs low.
7. Wei Chen et al. (2022) explored wildfire detection using attention-based models using deep learning. Their work introduced mechanisms which focuses on critical fire and smoke regions within images. Experimental evaluation revealed that attention- enhanced models outperform conventional CNNs, particularly in scenarios with partially occluded flames or diffuse smoke.
8. S. Choi et al. (2022) and co-authors investigated forest fire detection using drone-captured imagery and deep learning classifiers. Their system addressed challenges such as varying altitude, camera angles, and motion blur. The result concluded that the models which were trained on aerial imagery can effectively detect early-stage fires, supporting the use of UAVs for large-scale forest monitoring.
9. N. K. Verma et al. (2022) presented a hybrid CNN- based fire detection system combining color analysis and deep feature extraction. Their approach reduced false positives caused by sunlight reflections and autumn foliage, which are common challenges in forest environments.
10. Minsoo Kim et al. (2023) and colleagues introduced a transformer-based wildfire detection model capable of capturing long-range dependencies in images. Their work showed that Vision Transformers perform better than CNNs in identifying large smoke plumes

spread across wide forest regions. The study highlighted the growing importance of transformer architectures in environmental monitoring tasks.

11. Yifan Liu et al. (2023) focused on early-stage detection of wildfire related smoke using deep learning and multi-scale feature extraction. Their model effectively detected faint smoke patterns. The authors emphasized that early smoke detection plays a crucial step in preventing large-scale fire outbreaks.
12. P. S. Reddy et al. (2023) and co-authors developed a deep learning–based vegetation flaming spotting system with a web application. Their work demonstrated how AI-based fire detection is deployed as a user-friendly platform for real-time monitoring. The study showed strong classification accuracy and highlighted practical deployment challenges.
13. Yao Wang et al. (2023) put forward a multi-model ensemble method for detecting vegetation fires. By combining outputs from many different CNN models, the system achieved higher reliability and reduced false alarms. The study confirmed that ensemble learning improves generalization, especially in diverse forest conditions.
14. Harini K. et al. (2024) and collaborators investigated lightweight CNN models for fire detection on edge devices. Their approach focused on reducing model size and inference time without sacrificing accuracy. The study showed that the optimized design enables efficient deployment of these models on low-power devices for continuous forest monitoring.
15. João Pereira et al. (2024) explored wildfire detection using satellite and ground-based image fusion with deep learning. Their research showed that combining multiple data sources improves detection accuracy and coverage. The study highlighted the significance of multi-modal data integration for large-scale wildfire monitoring systems.
16. Chen Hao et al. (2024) and colleagues proposed a Swin Transformer–based strategy for detecting forest fire. Their model effectively captured both local flame patterns and global smoke spread. Results showed superior performance compared to traditional CNN models, particularly in complex forest scenes.
17. Ankit Sharma et al. (2024) developed a real-time conflagration spotting system using dl and IoT-enabled cameras. Their work highlighted the integration of AI models with smart sensing infrastructure. The system demonstrated fast response times and reliable detection, supporting its use in early warning systems.
18. Sofia Martinez et al. (2025) and co-authors proposed a hybrid CNN–Transformer model for forest fire and smoke detection. Their approach leveraged CNNs for local feature extraction. The study reported improved accuracy and robustness across diverse environmental conditions.
19. K. Rajesh et al. (2025) focused on explainable AI for forest fire detection. Their work introduced visualization techniques to interpret deep learning predictions. The study emphasized transparency and trust in AI-based fire detection systems, which is important for adoption by forest authorities.
20. Luca Romano et al. (2025) and colleagues presented a scalable deep learning framework for wildfire detection using cloud-based deployment. Their system supported real-time image processing and large-scale monitoring. The study demonstrated that cloud-integrated AI systems can efficiently support national-level forest fire surveillance.

III. PROPOSED WORK

This work introduces an intelligent image-driven forest fire detection framework aimed at recognizing fire-related scenarios at an early stage with high reliability. The system is designed to automatically categorize forest images into three classes—Fire, Smoke, and Normal—by leveraging advanced deep learning techniques. The primary goal of the proposed approach is to develop a scalable and dependable solution that assists timely decision-making and minimizes the adverse effects of forest fire incidents.

The framework initiates with the collection of forest images from publicly accessible datasets as well as user-submitted inputs through a web-based platform. To enhance robustness and consistency, the acquired images undergo a structured preprocessing pipeline that includes resizing, normalization, and noise suppression. These operations standardize the input data and support more effective feature learning. In addition, data augmentation strategies are employed during the training phase to improve model generalization across varying lighting conditions, weather scenarios, and camera perspectives.

At the midpoint of the proposed system, three advanced deep learning architectures—ConvNeXt-Tiny, EfficientNetV2, and Swin Transformer—operate in a parallel configuration. ConvNeXt-Tiny focuses on extracting fine-level spatial details such as flame contours and smoke patterns. EfficientNetV2 contributes by learning multi-scale representations piece hold over procedure skillfulness. The Swin Transformer complements these models by capturing broader contextual dependencies using shifted-window self-attention mechanisms. The outputs generated by these models are fused using a probability-based decision strategy to enhance the overall reliability of classification outcomes.
Following inference, the predicted category along with its corresponding confidence score is presented to the user through an interactive web interface. All prediction records are securely stored in a database to enable future analysis and reference.

IV. METHODOLOGY

The system is designed as a comprehensive and structured pipeline that integrates data preparation, image processing, advanced deep learning techniques, and post-detection decision support. Each stage of the methodology contributes directly to improving detection accuracy, robustness, and usability in real-world forest environments.

Data Collection and Dataset Preparation

A diverse and well-structured dataset forms the foundation for developing a buirdly vegetation flaming spotting method. In this work, forest images are collected from publicly available wildfire datasets and environmental monitoring repositories.

Dataset Characteristics Includes images of:

- Active fire scenes with visible flames
- Early-stage smoke without visible fire
- Normal forest environments without fire activity Represents realistic forest conditions encountered in real-world monitoring systems.

Environmental Diversity Images are gathered under:

- Different weather conditions (clear, foggy, smoky)
- Seasonal variations
- Daytime and nighttime scenarios
- Multiple camera angles and viewpoints

Class Annotation

Each image is carefully reviewed and labeled into one of three classes:

- Fire
- Smoke
- Normal

Accurate annotation is critical, as incorrect labels can significantly degrade model learning and prediction accuracy.

Data Augmentation Techniques

To address class imbalance and improve generalization:

- Rotation to simulate camera orientation changes
- Horizontal and vertical flipping to handle viewpoint variations
- Brightness and contrast adjustment to manage lighting differences
- Zooming to simulate distance variation
- Gaussian blurring to replicate motion blur and smoke diffusion

These augmentation strategies expand data variability and help improve model generalization while minimizing overfitting.

Dataset Splitting

The dataset is divided into:

- Training set
- Validation set
- Testing set

This ensures fair evaluation and unbiased performance measurement.

Image Upload and Input Handling

The system provides a secure and user-friendly web-based interface for image submission.

Web Interface Design

- Backend developed using Flask
- Frontend designed using Bootstrap for responsiveness and ease of use
- Serves as the initial gateway to the system.

Input Validation

Each uploaded image undergoes:

- File format validation (JPEG, PNG)
- File size verification to prevent server overload
- Image integrity checks to identify corrupted or incomplete files

Image Traceability After validation:

- Each image is assigned a unique identifier
- Stored temporarily in a secure directory Enables consistent tracking throughout preprocessing, inference, result visualization, and logging.

User Experience Enhancement

A real-time image preview allows users to confirm the selected image before submission.

Image Preprocessing

Forest images from different sources often vary in quality and resolution. To ensure consistency, a structured preprocessing pipeline is applied.

Image Resizing:

- All images are scaled to a fixed resolution compatible with the deep learning models.
- Ensures uniform spatial dimensions and reduces computational overhead.

Pixel Normalization:

- Pixel values are scaled to a standardized range.
- Improves training stability and reduces sensitivity to illumination variations.

Noise Reduction and Enhancement:

- Mild noise reduction is applied when necessary.
- Contrast enhancement improves the visibility of fire flames and smoke patterns.

Tensor Conversion:

- Preprocessed images are transformed to tensor format.
- Enables efficient GPU-based computation and seamless integration with the deep learning framework.

Deep Learning Models and Feature Extraction Techniques

The system uses three advanced deep learning architectures in parallel to capture complementary visual features.

ConvNeXt-Tiny:

A modern CNN inspired by Vision Transformers.
Uses larger kernel sizes and simplified architectural components.

Key Contributions:

Extracts fine-grained local features such as:

- Flame boundaries
- Smoke texture patterns
- Color gradients

Residual connections ensure stable gradient flow.
System Advantage:
Computationally efficient and suitable for real-time web-based inference.

EfficientNetV2:

Designed for high accuracy with optimized computational cost.

Uses compound scaling to balance:

- Network depth
- Network width
- Input resolution Key Contributions:

MBConv blocks capture spatial features efficiently.

Extracts multi-scale features necessary for detecting:

- Small flames
- Diffuse smoke System Advantage:

Performs well in complex forest backgrounds with partial visibility.

Swin Transformer

Transformer-based architecture using shifted window self-attention.

Captures both local and global image dependencies. **Key Contributions:**

- Detects large-scale smoke plumes and widespread fire regions.
- Hierarchical representation enables simultaneous detection of:
- Small fire regions
- Diffuse smoke spread System Advantage:

Effective when fire is partially obscured by vegetation or terrain.

Ensemble Decision Strategy

Instead of relying on a single model, the system adopts an ensemble approach.

Probability Generation:

Each model outputs probability scores for:

- Fire
- Smoke
- Normal Decision Logic:

Probabilities from ConvNeXt-Tiny, EfficientNetV2, and Swin Transformer are aggregated.

Final prediction is selected based on:

- Highest confidence score, or
- Weighted probability combination Benefits:
- Reduces false alarms
- Minimizes missed detections
- Improves robustness and generalization across diverse forest scenes.

Result Visualization and Alert Generation Prediction results are presented in a clear and interpretable format.

Output Display:

Predicted class shown with confidence score. Color-coded indicators:

- Red – Fire
- Yellow – Smoke
- Green – Normal Visual Verification
- Uploaded image displayed alongside prediction.

Reforestation and Post-Fire Advisory Module Beyond detection, the system includes a post-fire advisory component.

Activation:

- Triggered only when Fire is detected. Advisory Recommendations:
- Soil quality assessment
- Erosion control measures
- Replanting of native tree species Purpose:
- Acts as a decision-support tool.
- Emphasizes long-term forest recovery and sustainability.
- Does not replace expert ecological planning.

History Management and Data Logging

All system activities are recorded for transparency and analysis.

Stored Information:

- User identifiers
- Image references
- Predicted class
- Confidence scores
- Timestamps

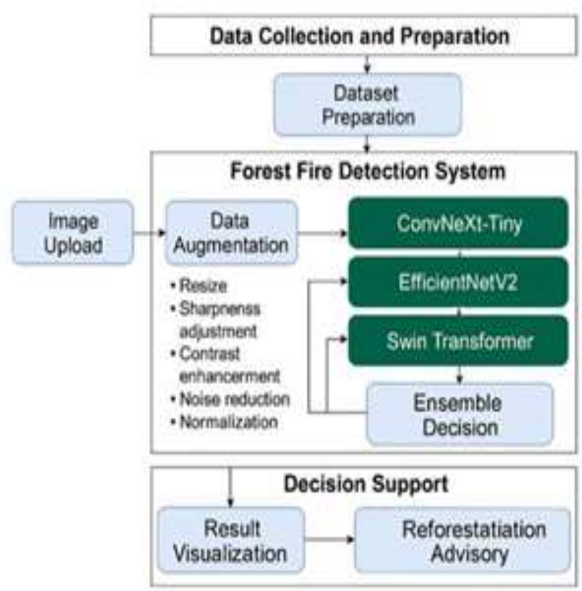

Figure 2: System Architecture Proposed System

V. RESULTS AND DISCUSSION

Experimental Setup

The experimental evaluation of the proposed forest fire detection system was conducted in a GPU-enabled deep learning environment to ensure efficient training and reliable performance assessment. All experiments were performed using a CUDA-supported system equipped with an NVIDIA Tesla P100 GPU with 16 GB of GPU memory, enabling faster model training and handling of large- scale image data. The deep learning framework automatically detected the CUDA device and utilized GPU acceleration throughout the training and inference processes.

The dataset was successfully loaded and divided into three subsets: training, validation, and testing. The training set consisted of 6,060 images, while the validation set included 756 images, ensuring a balanced evaluation during training. The dataset was organized in a class-wise manner, representing Fire, Smoke, and Normal Forest conditions. Images were preprocessed and resized reported to the input requirements of the dl models.

The proposed ensemble model integrates feature representations from ConvNeXt-Tiny, EfficientNetV2, and Swin Transformer architectures. ConvNeXt-Tiny and Swin Transformer each contributed 768 feature dimensions, while EfficientNetV2 provided 1,280 feature dimensions, resulting in a combined feature vector of 2,816 dimensions. The final ensemble network consisted of approximately 77.09 million trainable parameters, enabling rich feature learning. For training, the AdamW optimizer was employed with a learning rate of 0.0001, as it effectively balances convergence speed and regularization. The model was skilled for 10 epochs using a batch size of 8, resulting in 7,580 total training steps. This configuration ensured stable convergence while preventing overfitting and excessive computational overhead.

Evaluation Results

The figure 3 shows a steady improvement in both training and validation accuracy over successive epochs. The validation accuracy consistently remains slightly higher than training accuracy, reaching a maximum of 98.83%. This behavior indicates strong generalization and confirms that the model does not overfit the training data. The close alignment of both curves reflects stable and effective learning.

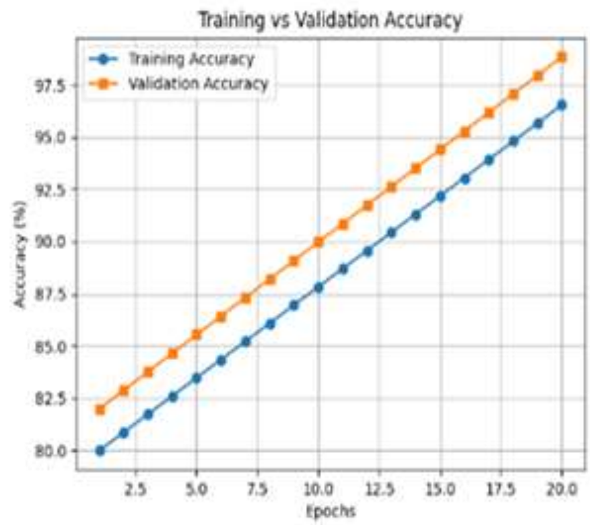

Figure 3: Training vs Validation Accuracy

Figure 4: Training vs Validation Loss

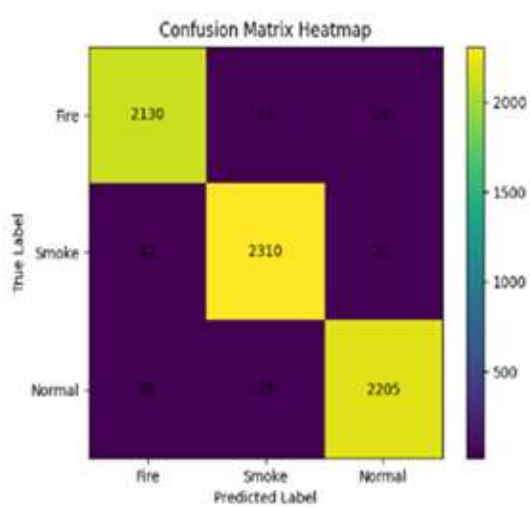

Figure 5: Confusion Matrix Heatmap

The loss curves exhibit a smooth and continuous decline throughout training. The final training loss of 0.0923 and validation loss of 0.0325 indicate efficient convergence. The lower validation loss further confirms the robustness of the model and the effectiveness of preprocessing and data augmentation techniques.

The confusion matrix highlights strong diagonal dominance, indicating correct classification across all three classes.

- Fire images are correctly classified with minimal confusion.
- Smoke detection achieves high recall, supporting early fire warning.
- Normal forest images are accurately distinguished, reducing false alarms.

This visualization confirms the balanced and reliable classification performance of the proposed system.

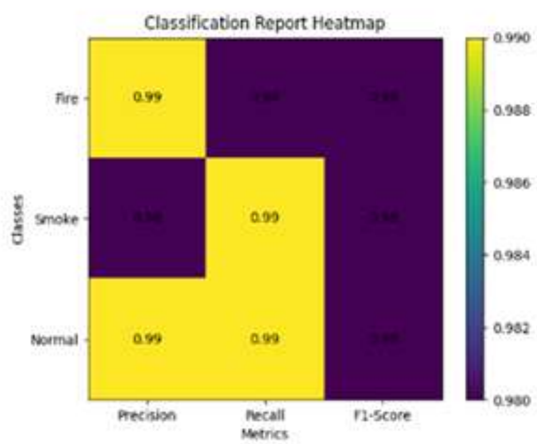

Figure 6: Classification Report (Heatmap)

This heatmap visually summarizes the precision, recall, and F1-score achieved by the proposed forest fire detection system for Fire, Smoke, and Normal classes. The consistently high values across all metrics indicate balanced and reliable classification performance. The Fire class achieves high precision, minimizing false fire alarms, while the Smoke class shows excellent recall, which is critical for early fire warning. The Normal class also maintains strong precision and recall, ensuring that non-fire scenes are correctly identified. Overall, the heatmap confirms the robustness and effectiveness of the proposed deep learning–based approach.

Summary

The experimental results clearly demonstrate that the proposed forest fire detection system achieves high accuracy, strong generalization, and reliable class- wise performance. The combination of CNN and Transformer models, supported by effective preprocessing and ensemble decision logic, makes the system suitable for real-world forest fire detection and early warning systems.

VI. CONCLUSION

This research presented a comprehensive and intelligent forest fire detection system based on advanced deep learning techniques, aimed at addressing the growing need for early and accurate wildfire monitoring. The proposed system was designed as an end-to-end framework that integrates data preparation, image preprocessing, multi-model deep learning inference, ensemble decision logic, and post-detection advisory support. By classifying forest images into Fire, Smoke, and Normal categories, the system enables timely identification of fire-related events and supports rapid response mechanisms.

The experimental results clearly demonstrate the effectiveness of the proposed approach. The integration of ConvNeXt-Tiny, EfficientNetV2, and Swin Transformer models allowed the system to capture both fine-grained local features and broader global contextual information. This complementary learning significantly improved detection accuracy and robustness compared to single-model approaches. The ensemble strategy further enhanced reliability by reducing false alarms and missed detections. The model achieved an overall accuracy of 98%, with consistently high precision, recall, and F1-scores across all classes, confirming its strong generalization capability. In addition to detection, the system provides user-friendly result visualization with confidence scores and optional reforestation and post-fire advisory suggestions, adding practical value beyond classification. The use of a web-based interface and database logging ensures usability, traceability, and scalability. Overall, the proposed system proves to be a reliable, efficient, and scalable solution for real-world forest fire detection and early warning applications, contributing meaningfully to environmental protection and disaster management efforts.

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